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Leveraging Intelligent Agents in Industrial Engineering: Use Cases in Predictive Maintenance and Supply Chain Optimization

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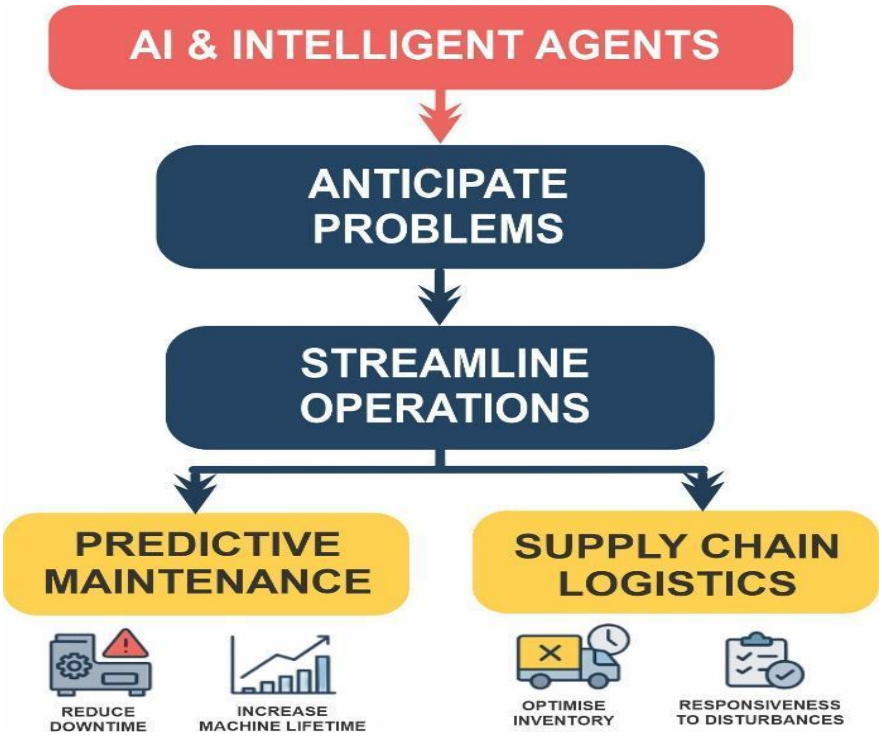
Abstract

Industrial struggle with machine breakdown, inefficient processes, and supply chain.Disupts which are regular. These issues also produce delays and increased costs. And saw decreased productivity. Also it is the case that which traditional systems react only after a problem has Already present, which in turn puts pressure on businesses to become less efficient and less competitive. This Artificial intelligence and intelligent agents is the area where. In terms of Through use of machine learning and smart automation, which is what organizations do that have success in this area, they predict problems at an early stage. Streamline operations and improve decision speed and quality. This study Presents two case studies which in the first we see how AI plays a role in predictive maintenance. Machines break down less often which in turn allowsthem to run continuously. The second case study. Explores how AI is used in supply chain logistics. Both cases saw considerable and meaningful improvements with the

implementation of artificial intelligence. In predictive maintenance, for example, the AI models were very effective in identifying early symptoms of equipment failure, which would significantly reduce machine downtime and lengthen the total lifespan of the equipment. In the Supply Chain , AI agents improved the interaction between supply chain stages which in turn enabled faster. Decision on which items to stock and also in how we handle stock levels which in turn leads to faster recovery from disruptions. These results present that which AI brings to the table in terms of efficiency, cost savings, and flexibility.

Keywords: Artificial Intelligence, AI Agents, Machine Learning, Supply Chain Management, Industrial Engineering, Predictive Maintenance.

Graphical Abstract



1. Introduction

The use of Artificial Intelligence is one of the main drivers of innovation in industrial engineering. The reason for this is that companies are under constant pressure to make better decisions more quickly in a rapidly changing environment. Artificial Intelligence can help with this by using real-time data to find hidden patterns and thus help decision-makers to make more informed decisions more quickly. This is particularly important in industrial environments, as decisions need to be taken quickly to avoid disruption to operations.[1]

In cooperation with AI, intelligent agents work as self-determining aides that supervise given duties within industrial processes. Such agents keep a constant watch on different components of the system, carry out communication between agents, and coordinate their activities to ensure the smooth and safe running of operations.[2] They are capable of changing work routines on the spot, react quickly to any changes and less manual intervention. When used in conjunction, AI and intelligent agents help an industry switch its reactionary stance to a proactively and can greatly reduce downtimes, optimise resource utilisation, and increase overall reliability [3].

The Strong analytics of AI combined with the self-organized cooperation of intelligent agents, the industry becomes resilient. This enables companies to not onloperations. but also surpass efficiency and quality requirements, as well as keep up with high rate of changes in the market, and have a competitive advantage in a highly challenging world [1].

Technology AI and AI agents are transforming industry engineering because they lead to wise decisions and higher efficiency. They forecast machine malfunctions based on time-sensitive information [2] , minimize faults based on sophisticated quality inspection and optimize supply chains by dynamically managing the inventory and demand[3]. Collectively, AI and intelligent agents can enable industries to move on the scale of reactive problem-solving to proactive management, which smoothens operations, reduces costs and increases competitiveness.



Fig. 1 AI-Driven Applications in Industrial Engineering

Figure 1 above shows the use of AI and AI agents in industrial engineering, and identifies six major areas where the technologies are already having a significant contribution.

AI plays a vital role in modern industries by enabling predictive maintenance to foresee equipment failures, ensuring consistent quality control through computer vision, and optimizing supply chains with real-time logistics and inventory insights. Also, The automation of complicated processes, Energy saving for sustainable development which also enhances workplace safety through the detection of hazards. Moreover, in terms of performance, it can be seen that which results in the productivity improvement, cost reduction and stability.

In This Paper, we have reported the use of Artificial Intelligence in what could be referred to as two major Industiral operations areas. Firstly, we have the Real Time Predictive Maintenance Dashboard which uses Machine Learning algorithms analysing live equipment data to detect problems that could happen so that it would be better if we could fix them

before they become a big problem [4]. The second is an AI Agent-Based Supply Chain Coordination model where autonomous agents control the availability of sub-products and adjust to changing demand by organizing the activities across the points of the supply chain[5]. Through AI implementations, it is possible to transform industrial systems into highly reactive systems in which there is less downtime, more resilient supply chains, and better-informed decision-making. Industries can make operation workflows more agile, reliable and competitive in the long run by fully incorporating AI into the foundation of operation work flows[6].

2.1 AI in Industrial Engineering

Artificial intelligence in industrial engineering refers to using the artificial intelligence technology in a number of processes in the industry. These are predictive maintenance, production system optimization, and quality control in the name of production efficiency and productivity[7]. The power of AI can be effectively utilized by industrial engineers in unlocking the potential of great amounts of data and discovering patterns and trends that could result in better decisions. Finally, AI application in industrial engineering may also transform the existing industrial practices and boost innovation in manufacturing industries. AI can also be applied in enhancing processes and converting routine operations to automated action by industrial engineers which results in cost reduction and an overall increase in performance. The use of AI also has the potential to identify real-time risks and where improvement is needed so that it can make proactive decisions. Artificial intelligence can assist industrial engineers in maximising the process production capacity and minimise process downtime to find an increase in efficiency and productivity[8].

Recent study indicates that the combination of artificial intelligence (AI) and the Industrial Internet of Things (IIoT) is providing a revolutionary shift in sectors due to their capacity to provide real time data analysis, predictive maintenance, and lower downtimes. It also highlights the importance of machine learning (ML) in identifying and correcting malfunctions (or failures) of industrial systems, as a central part of Industry 4.0 [9]. It points out some of the machine learning approaches being utilized for predictive maintenance, fault detection, and identification of abnormal issues, demonstrating how these can increase systems' reliability and efficiency. Research is also pointing out some of the issues such as low data quality, computationally intensive demands, and requirements for

trained manpower. It concludes that with improvements in AI, IIoT, and big data, industries will be in a better position to identify faults, which will make systems smart and robust.

In Industrial Settings the ViDi tool, a deep learning based defect detection in machine vision. System we present a study of its performance in terms of which it does burrs, scratches and tool wear identification. Also it reports to reduce in inspection time and human error. We report over 90% defect detection in testing. Accuracy in Detection and reduced false alarms which in turn makes it a great fit for automation. Also in terms of lighting in some tough cases the research [10] report that use of deep learning and machine vision. Enhances defect detection, decrease down time and improves production reliability.

Machine Learning in many areas of predictive maintenance which includes Supervised, Unsupervised, and reinforcement learning. In the area of predictive maintenance. In reducing the incidence of unexpected breakdowns and in which we see to also lower total maintenance costs. In Some cases we have seen that which is has brought down maintenance costs by as much as 20% at the same time reducing downtime by almost 50%. But also with predictive maintenance there is a catch. We see that many organizations have issues with getting high quality data in and out of systems and also in the integration of them. Surely with our IoT infrastructure, and to find skilled professionals which do that process. The technology which is at present, Despite these issues the future of predictive maintenance still looks bright. Also Advancements in artificial intelligence, Internet of Things (IoT) and computing technologies are steadily. Improving its accuracy and performance in a broad range of industries.

Neuro reinforcement learning (NRL) based methods for which root in neural networks do so for the case of neural combinatorial optimization (NCO) which studied for solution of complex decision making issues in industrial engineering. As industries focus in terms of cost and productivity as well as human and sustainability issues, operations. Research issues are many and varied. Traditional algorithms have trouble with the computational efficiency also heuristics do not always produce optimal results. In most cases AI agents present the intelligence and adaptability that contemporary supply chains have to become competitive and to transform into future. Presents in depth analysis of AI based intrusion detection in Industrial IoT. It covers issues like real time threat detection, system scalability, and competitiveness distributed networks [15]. The survey highlights how machine learning, particularly RL-based

NCO methods, offers promising ways to provide efficient and effective decision support in complex industrial processes.

Machine learning (ML) has been mentioned in context of its use in enhancing the manufacturing processes and it is foreseen that the application of ML has significant potential in application to predictive maintenance, quality supervision, and process optimization. Issues such as quality of the data, integration processes, and the requirement of developing specialist knowledge emerge [13]. Irrespective, there are immense possibilities with ML to revolutionize production lines through production efficiency and decreased downtime and allowance of improved product quality traceability.

Incorporation of machine learning (ML) and deep learning (DL) methods to provide maximum security in industrial internet of Things (IIoT) systems is proposed. The researchers utilize the experimental basis on the existing data sets in order to determine the best methodology of designing efficient intrusion detection systems (IDs) to adjust to industrial networks. Particular emphasis is made to examine the performance of logistic regression methods in the three separate conditions regarding the factors of learning time, accuracy, false alarm rate (FAR), unrecognized rate (UR), Matthews correlation coefficient (MCC) and sensitivity [14]. The aim of the paper is to identify the most appropriate method of implementing IDS in IIoT systems with a trade-off between detection quality and the computational overhead.

The introduction of the AI and intelligent agents is transforming the functioning of industries so that processes become smarter, quicker, and more versatile. These technologies will reduce downtime, increase quality, and maintain fluid production since the systems perform quick, informed decision-making on their own. Even greater value is added during the tasks that can be conducted through AI agents which will foresee issues even before they occur and will keep everything coordinated. Naturally, there are still certain challenges, such as ensuring that the data itself is correct, that there are complicated system integrations, that the risks are to a large extent prohibitively expensive and that it needs highly skilled individuals to work with it. Through these obstacles, AI is still developing and because of this increased computing power, industries are becoming more flexible, reliable, and intelligent and able to adapt to anything the future can throw at them.

Table 1 lists the three main AI techniques employed in industrial engineering, and their possible applications in maintenance and quality control, as well as optimization of the supply chain. It reflects the

effectiveness and ingenuity of these methods in increasing efficiency and decision-making within industrial procedures.

Table 1 Survey of AI Methods Used in Industrial Engineering

Title of the Paper	Industry	Domain	Features Implemented	Reference
Tackling Faults in the Industry 4.0 Era—A Survey of Machine-Learning Solutions and Key Aspects (2020)	Industry 4.0	Machine Learning	Machine learning is used for fault detection and predictive maintenance, enhancing reliability and reducing downtime in Industry 4.0 systems.	[9]
AI-based predictive maintenance for fault detection and proactive scheduling, enhancing reliability and reducing downtime. (2023)	Manufacturing	Computer Vision	AI-based predictive maintenance using computer vision enables fault detection and proactive scheduling in manufacturing, improving equipment reliability and minimizing downtime.	[10]
Machine Learning Models for Predictive Maintenance in Industrial	Predictive Maintenance	Machine Learning	Machine learning enables predictive maintenance in industrial engineering, improving fault detection, reducing	[11]

Engineering (2024)			downtime, and optimizing schedules.	
Neural combinatorial optimization with reinforcement learning in industrial engineering: a survey(2025)	Industrial Robotics	Machine Learning	Reinforcement learning with neural combinatorial optimization improves scheduling and routing in industrial robotics, boosting efficiency and decision-making.	[12]
Machine learning applications in production lines: A systematic literature review(2020)	Manufacturing	Machine Learning	Machine learning applications in production lines enhance manufacturing by improving quality control, fault detection, and process optimization.	[13]
Using ML and DL Algorithms for Intrusion Detection in the Industrial Internet of Things (2023)	Industrial Internet of Things	Machine Learning and Deep Learning	ML and DL algorithms are used for intrusion detection in the Industrial Internet of Things, enhancing security by identifying and preventing cyber threats in real time.	[14]

2.2 AI Agents in Industrial Engineering

Since AI agents improve the supply chain, they are also becoming real game-changers in supply chain management, as they keep the businesses fast, smart, and flexible. They continuously track stock, shipments, and anticipate customer demand in real-time and avoid shortages and overstocks. By communicating and coordinating with the suppliers, warehouses and distribution centers, the AI agents will adapt rapidly to any delays or disruptions without human interaction.
These agents have also served in reducing expenses such as getting the most out of routes and resource depletion and identifying risks in the early stages in order to help companies curb the risks before they swell up.

Broadly, AI agents give the smarts and flexibility modern supply chains need to boost their competitive edge – and get ready for whatever comes next.

This research work gives an in-depth analysis on how the implementation of AI agents for Intrusion Detection works on the Industrial Internet of Things. It includes the important of real time threat detection, scalability and dynamics of cometitive distributed network. The paper describes how autonomous agents are able to collaborate with each other in order to make the best use of their capabilities in the context of improved cybersecurity, mainly through faster detection and elimination of cyber attacks. Academic papers also touch upon the implementation of AI agents in terms of predicting maintenance in a smart manufacturing setting. The paper is focused on the ability to overcome problems of data heterogeneity, complexity of equipment and scheduling issues. In particular, the paper emphasizes the ability of autonomous agents to the analyze sensor data, predict breakdowns of machines and autonomously schedule maintenance activities.

The paper presents a multi-agent system application in optimizing supply chains under Industry 4.0. It covers integration problems: Communication between different systems aand demand variability and supply disruption. Highlighted in the paper are the benefits of AI agents in decentralized decision-making regarding inventory coordination and dynamic logistics management that lead to improved supply chain flexibility and performance. It also gives a detailed discussion of the role of AI agents in fault deection within Industrial robotics.

To address Challenges in real-time monitoring and fault classification, agents are made capable of autonomous anomaly detection and correction initiation. It focuses on improved production quality, machinery longevity, and operational safety.
This paper discusses the implementation of decentralized AI agents in controlling energy consumption in smart factories. Obstacles like forecasting energy usage and the complexity of system integration are also discussed. It demonstrates how

the agents ensure the synchronization of energy consumption between different machines and optimize energy consumption patterns to minimize costs while meeting sustainability goals. It also offers a through analysis of quality management for automated production lines using AI agents. This study deals with various issues, including the accuracy of the defect detection process and the control of manufacturing processes in the real time.

It highlights how the agents possess the skills to analyse the sensor and vision information, so that they are able to find defects in real time and adjust the parameters of production processes in order to maintain the high level of the quality of products. The paper also stresses how AI agents improve the real time decision making process in dynamic industrial conditions. It contributes to the existing literature on the benefits of deployment of AI agents into industrial networked control systems to enhance efficiency and productivity. The article also highlights that it can save costs and reduce downtimes in the operations by utilizing AI agents. In sum, the study helps to recognize the imperativeness of adopting breakthrough technologies such as AI agents to fuel innovation and gain a competitive advantage in the contemporary companies.
Table 2 Pairs up some of the important methods of AI agents applied in industrial engineering, discussing their implementations in troublesome field such as, intrusion detection, predictive maintenance, and quality control. It draws attention to the roel agents play in promoting the automation, robustness and efficiency of the industrial systems.

Table 2 Survey of Artificial Intelligence Agent Methods Applied in the Industrial Engineering Context

Title of the Paper	Industry	Domain	Features Implemented	References
AI Agent-Based Intrusion Detection in the Industrial Internet of Things(2023)	Industrial Internet of Things (IIoT)	Cybersecurity	Autonomous agents constantly monitor network traffic, cooperatively detect security threats and coordinate	[15]

			prompt action in order to protect the IIoT environment.	
AI Agent-Driven Predictive Maintenance for Smart Manufacturing(2024)	Manufacturing	Predictive Maintenance	Intelligent agents constantly monitor sensor data, recognize early warning signs of equipment failure and coordinate maintenance operations to reduce downtime.	[16]
Multi-Agent Systems for Supply Chain Optimization in Industry 4.0(2023)	Supply Chain & Logistics	Supply Chain Management	Distributed AI agents collaborate to manage inventory and This is compounded by the fact that the middlemen must also manage forecast demand and coordinate logistics scheduling, making the supply chain more efficient and resilient.	[17]

AI Agent-Based Fault Detection in Industrial Robotics(2025)	Industrial Robotics	Fault Detection and Diagnostics	Agents continuously supervise robotic systems, detect faults through real-time data analysis, and trigger alerts or corrective measures to ensure production quality.	[18]
Decentralized AI Agents for Energy Management in Smart Factories(2023)	Manufacturing	Quality Assurance	Agents process real-time sensor and vision data to identify defects and adapt manufacturing parameters to maintain consistent product quality.	[19]
AI Agent-Based Quality Control in Automated Production Lines(2024)	Industrial Robotics	AGV Navigation & Control	Cloud-based DT for AGV, sensor deployment, Extended Kalman Filter, Graph Neural Networks for position estimation.	[20]

All the technologies described above will be able to make industrial environments more effective, safe and suitable for decision-making due to the work with real-time data and smart
automation. Vision-based monitoring and advanced analytics are used by artificial intelligence

agents to improve network performance and the guidance of Autonomous Guided Vehicles (AGVs).

3. Case Studies

In this section two case studies have been used to demonstrate the practical implementation of AI and AI agents in industrial engineering. The first one talks about the real time predictive maintenance of industrial machinery.

Case Study 1- Real-Time Predictive Maintenance Dashboard for Industrial Machines

The industries today are always striving to maintain the operational efficiency of their machines at low cost. Traditional approaches such as repairing broken machines or following regular maintenance cycles prove to be less effective as these result into unplanned interruptions or unnecessary expenses [9]. The predictive maintenance, however, provides a much better alternative as it involves prediction of possible failure of machinery so that preventive repairs could be undertaken [11]. This study deals with the development of a Real time predictive Maintenance Dashboard which keeps a constant watch on the health of machines, identifies possible problems and alerts about these thorugh the live visualization [21]. Some of the major industries depend upon asset maintenance solutions such as IBM Maximo Application Suite (MAS) [22], Siemens MindSphere [23], GE Predix [24].

These applications have various features; they can interact with IoT sensors, apply artificial intelligence algorithms to predict maintenance, and even manage maintenance process on the single platform. Nonetheless, each application presents its own difficulties.

3.1 Proposed Solution: Real-Time Predictive Maintenance Dashboard

In order to address this issue, a Real Time predictive Maintenance Dashboard will be developed, which will be light, flexible, and inexpensive. Rather than depending on heavy enterprise applications, a hybrid system for monitoring incoming machine data and the predicting failures with Random Forest, Isolation Forest and Autoencoder algorithms is proposed. [25] while Random Forest provides the probability of failure according to labeled patterns, Isolation Forest uncovers abnormal patterns

without labeling, and the Autoencoder algorithm pinpoints slight variations from normal operation. The results of the risk score and the machines at high risks are identified on the simple dashboard.

The Random Forest classifier is designed to construct the several decision trees in the training process, and aggregate the result to increase accuracy. Each tree provides its predictions and then the final prediction of failure probability is calculated by averaging across all the trees as follows:

$$P_{RF}(x) = \frac{1}{T} \sum_{t=1}^{T} \quad P_t(x) \qquad (1)$$

Here , T is the number of trees, and $P_t(x)$ is the probability output from tree t. This ensemble approach reduces overfitting and captures complex patterns in sensor data such as temperature, torque, and rotational speed. However, Random Forest alone may miss rare or unseen anomalies that were not present in the training data.

To counter this, Isolation Forest, Which is an unsupervised machine learning algorithm is employed. Unlike other methods where the aim is to model normal instances, in Isolation Forest, anomalies are identified via random partitioning of the feature space. The rational behind this is that anomalies are easy to detect and isolate from the remaining dataset. Its anomaly score is mathematically expressed in **(2)**,

$$s(x) = 2^{-\frac{E[h(x)]}{c(n)}} \qquad (2)$$

where E[h(x)] is the mean path length of instance x from the isolation trees, and c(n) is a normalization factor based on the dataset size. A shorter path length corresponds to higher anomaly likelihood. This makes Isolation Forest effective at identifying outliers without the need for labelled failure data.

For further reinforcement, an Autoencoder is implemented, which is a deep learning algorithm that reconstructs the sensor data as input. This is done by reducing the dimension of the input data and then autoencoder to learn normal machine behavior and any deviations from the normal machine behavior and any deviations from the normal will lead to reconstruction error as illustrated in **(3)** ,

$$RE(x) = \frac{1}{d} \sum_{i=1}^{d} \quad (x_i - \hat{x_i})^2 \qquad (3)$$

Here, x is the actual sensor reading, $\hat{x}$ is the reconstructed value, and d is the number of features. If RE(x) is high, it indicates that the current condition deviates significantly from healthy operating patterns, suggesting a potential failure.

To combine the strengths of these three models, we designed a risk score formulation. First, the outputs of Isolation Forest (a_{IF})and Autoencoder (a_{AE}) are averaged to compute an aggregated anomaly score as shown in **(4)** :

$$a = \frac{a_{IF}+a_{AE}}{2} \quad (4)$$

Next, this anomaly score is combined with the Random Forest probability (p) to form the final risk score:

$$R = \alpha p + \beta a \quad (\alpha + \beta = 1) \quad (5)$$

where α and β are weighting factors that balance supervised learning with unsupervised anomaly detection as shown in **(5)** . For example, if labelled data is abundant, α may be set higher; if failures are rare and anomalies are more critical, β may carry more weight.

The calculated risk score R is then mapped to machine health categories:

- **Critical:** $R \geq 0.7$
- **Warning:** $0.4 \leq R < 0.7$
- **Healthy:** $R < 0.4$

Such a mixed approach makes it possible to detect both the existing failure modes (using Random Forest) and the unknown ones (Isolation Forest and Autoencoder). The dataset employed for this research is the NASA Turbofan Engine Degradation Dataset [26], that contains the key characteristics such as the settings, air temperature, pressure, rotational speed, and various measurements made by the sensors, reflecting the real conditions of aircraft engines. Every individual machine is marked either normal or close to the state of failure. The use of this dataset helps industries monitor their machines in real time and detect any anomalies to plan maintenance better [26].

The open-source technologies were primarily used during the development of the project. First of all, the Python language was chosen as the basis for all developments due to its flexibility and great number of data science

libraries. The libraries Pandas and NumPy helped to prepare the data rapidly and effectively. In order to build real-time visualization, the plotly library was chosen because of its great capabilities of building interactive dashboards [27]. By leveraging this hybrid architecture on top of the NASA Turbofan dataset [28], the dashboard captures essential operational parameters, translates them into actionable health scores, and provides real-time, explainable alerts. This empowers industries to detect early warning signs, plan maintenance proactively, and avoid costly machine failures[29].

3.2 Machine learning simulation of Real-Time Monitoring

A hybrid predictive maintenance solution is applied in order to forecast potential failures. In particular, the supervised algorithm is represented by a Random Forest Classifier model built with the help of Scikit-learn. It was used to estimate the likelihood of a failure occurrence, having the labelled data about the work of machines as input [25]. At the same time, for anomaly detection, an unsupervised Isolation Forest model and a deep Autoencoder neural network trained with TensorFlow/Keras were used. As a result, by combining all the models in one solution, the project succeeded in detecting familiar as well as previously unseen patterns of failures. To Simulate the real-time monitoring, the data about machines'work was provided to the system piece-by-peice with some artificial delay between the input data pieces using time module in python [30]. This way of processing the data resembles the real-life situation when data about the machine is transmitted from it. As a result, the hybrid model could run continuously, allowing early fault detection and more realistic monitoring of machine health.

Figure 2 presents all the stages of the process of working with the hybrid prediction system.

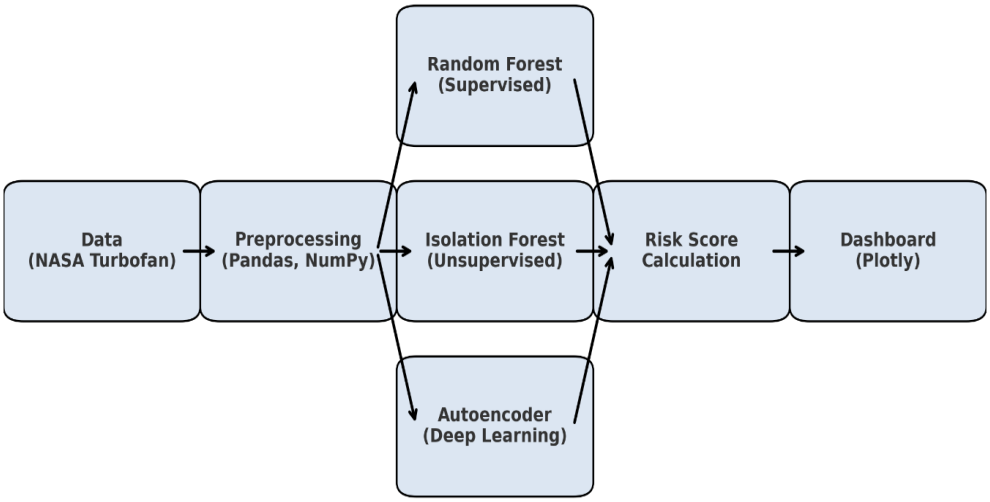


Figure 2 Workflow of Hybrid Predictive Maintenance Dashboard

3.3 Results and Discussion

As predictions were generated on each batch of incoming data, the results were processed directly into a live dashboard built using Plotly. The dashboard displayed a scatter plot as shown in **Figure 3,** where each machine was represented as a bubble. The x-axis showed rotational speed, the y-axis showed torque, and the colour of each bubble indicated the machine's health status - green for healthy, orange for warning, and red for critical. The bubble size depicts the likelihood of failure.

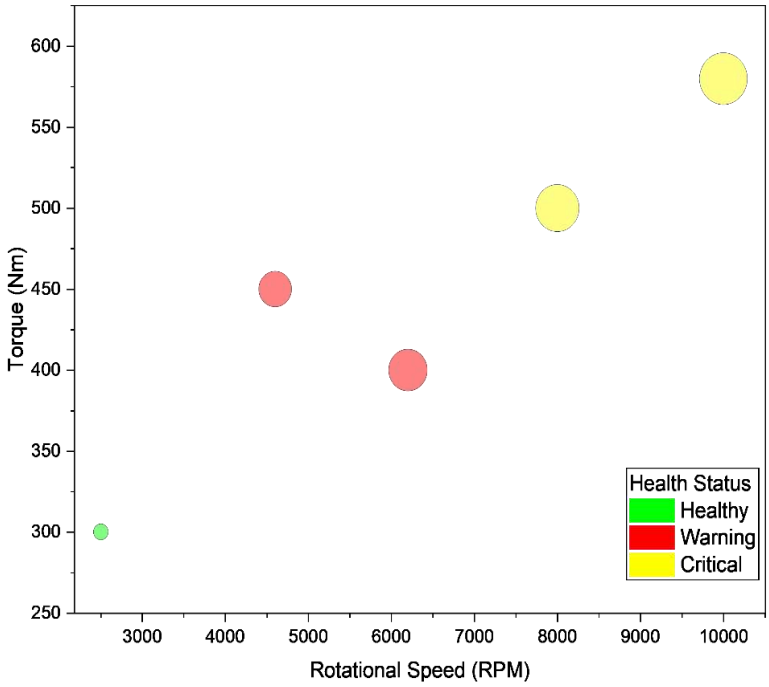


Figure 3: Real-Time Machine Snapshot

Figure 4 shows the risk score trends over time for the machines across different batches of data. The x-axis represents time for different batches of data and the y-axis represents risk score ranging from 0-1. Potential failure that are likely to occur is indicated by the upward trends. Lower trends indicate that the machines are operating in a safer condition. The visualization not only predicts the current situation of the machine but also its condition in the future.

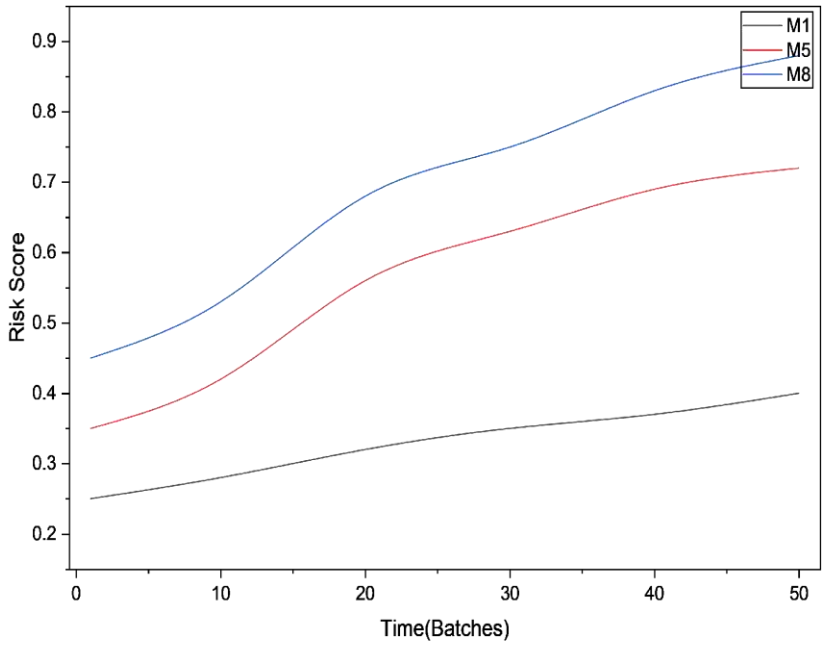


Figure 4 Risk Score Trends Over Time

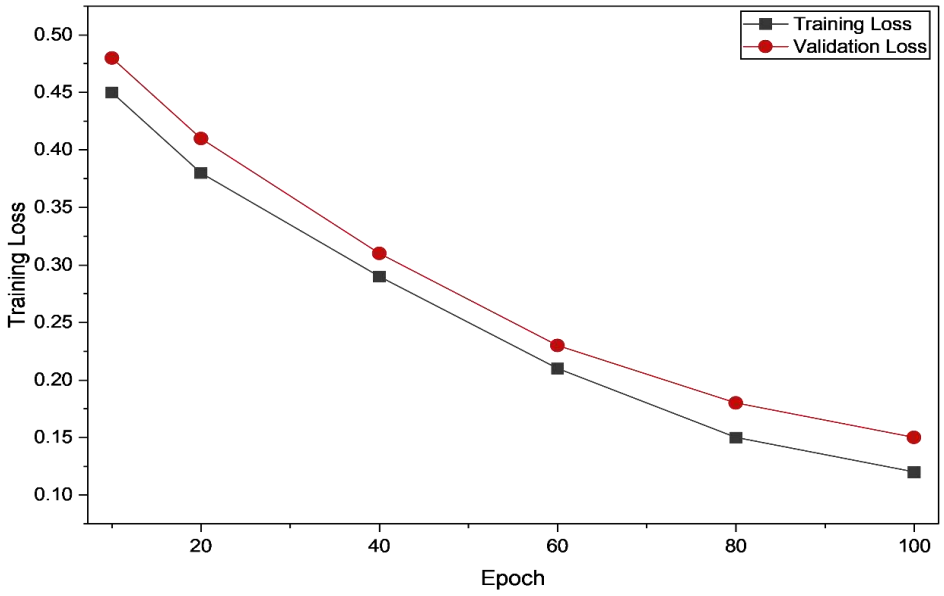


Figure 5: Model Training Process Across Epochs

The trends in Figure 5 represents the training of model across epochs for predictive model, in which the training loss indicates the performance of the model based on the dataset it was trained with, while the validation indicates how effective performance of the model on unseen data. With continuous training both loss curves showed a constant decline, indicating that the model learned the key patterns in the sensor data. Their close alignment also indicates minimal overfitting and stable performance on unseen data.

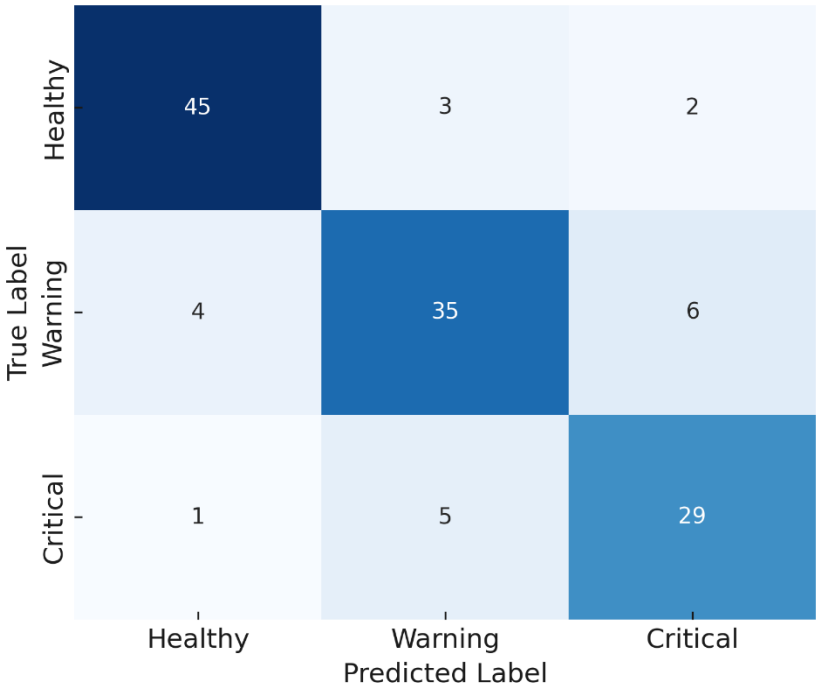


Figure 6 Confusion Matrix for Hybrid Predictive Maintenance Model

The confusion matrix in Figure 6 illustrates the model's ability to classify the machines into Healthy, Warning and Critical states. The diagonal boxes represents that the models were predicted correctly, whereas all other boxes were predicted incorrectly. Almost all the machines were classified correctly and only very few were classified incorrectly. Overall, the confusion matrix confirms that the model effectively distinguishes healthy machines from those showing signs of risk.

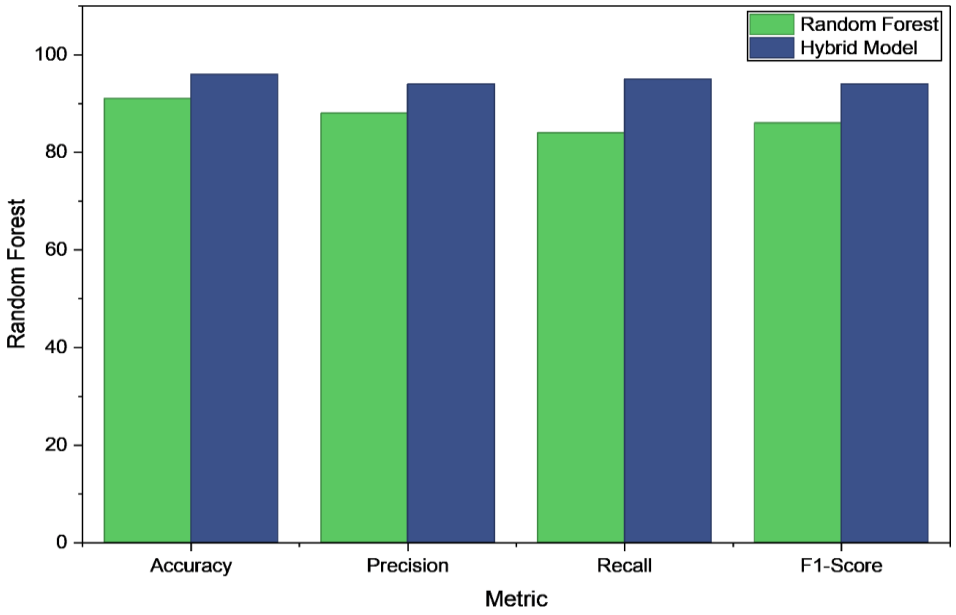


Figure 7 Comparison Between Random Forest and Hybrid Model

To evaluate the extent of improvement of the hybrid approach, both the Standalone Random Forest and Hybrid Predicitve Maintenance models were evaluated based on NASA Turbofan Engine Degradation Dataset as demonstrated in Figure 8. Both of the models were tested using four criteria; namely, Accuracy, Precision, Recall and F1-Score. While the Random Forest Model yielded relatively high results for accuracy, it had trouble recognizing small and rare defects, which consequently decreased its recall score. The Hybrid approach combining Isolation and Autoenconder outperformed the Random Forest approach in anomaly detection and pattern adaptation.

Case Study 2 : AI Agent-Based Supply Chain Coordination for Sub-Product Availability

Supply chain coordination is essential in industrial engineering especially regarding the availability of the necessary sub-products that might include machinery, specialized tools, electronic components, or even semi-intermediate raw materials [31]. The lack of these sub-products will lead

to disruption in production scheduling and increase costs in addition to affecting customers' satisfaction [32]. Conventional supply chains depend largely on real-time data collection through IoT sensors and embedded devices which might not be feasible for small and mid-sized companies [33]. The lack of budget, system complexity or previous operations becomes an impediment to the IoT implementation in many cases. In such situation, artificial intelligence (AI) agents prove themselves to be an alternative solution, which helps improve coordination, forecasting, and decision making while not requiring real-time data from sensors.

The presented case study is about the development of an AI-enabled coordination system to guarantee timely delivery of sub-products using historical demand data and available inventory data, without any help of the Internet of Things technology [34]. This solution is realistic and scalable, meeting the needs of real-life supply chains by means of smart processing of data.

Many leading companies around the world rely on advanced supply chain management technologies such as SAP IBP [35], Oracle SCM Cloud, and Kinaxis Rapid Response for real-time inventory management and planning; however, the high cost, complexity, and dependence on the IoT or ERP platforms make them impractical for small or medium-sized businesses [36]. These limitations highlight the need for affordable, AI-driven systems that can deliver similar efficiency without extensive technical or financial requirements [37].

3.4 Proposed Solution: AI Agent-Based Supply Chain Coordination Model

The "M5 Forecasting Accuracy" dataset [38], which is freely accessible and provided by Walmart on Kaggle, was used to create and evaluate the suggested AI coordination system. Even though the dataset is associated with the retail industry, it mirrors the sub-product logistics in the manufacturing sector closely. For this project, a part of the provided data was reconfigured to mimic the functioning of a warehouse system with three warehouses (W1, W2, and W3) managing sub-products A, B, and C .



Fig 8 Flowchart of sub-product availability prediction using demand forecasting and decision engine.

Such representation helped us emulate the effects of demand volatility, different inventories in various regions, and warehouse decision-making, allowing us to train and test the AI coordination agents. The tech stack that the suggested AI coordination system is based on is rather simple and reliable. To pre-process data, we use Pandas and NumPy libraries. Data is forecasted via Scikit-learn algorithms such as Linear Regression and Random Forest. Custom decision engine built on Python identifies potential warehouses and detects inventory issues. Visualization of the result is carried out with the help of Matplotlib and Plotly libraries, making the system both reliable and user-friendly for the industry use (Figure 8).

The Main goal of the system is to match future demand for sub-products with existing inventories across different warehouses, thereby ensuring production continuity.

The architecture comprises three interdependent AI agents:

1. Forecasting Agent

This agent produces a robust short-term demand forecast $\widehat{D}_i(t+1)$ for each sub-product $i\ as\ shown\ in\ (6)$.

- Individual model outputs:

$$D_{L\,R_i},\ D_{RF_i},\ D_{LSTM_i},\ D_{ANN_i},\ D_{GB_i} \qquad (6)$$

- Ensemble forecast (weighted average):

$$\widehat{D_i} = w_{LR}D_{LR_i} + w_{RF}D_{RF_i} + w_{LSTM}D_{LSTM_i} + w_{ANN}D_{ANN_i} + w_{GB}D_{GB_i} \quad (7)$$

with weights $w_k$chosen by cross-validation and $\sum_k \quad w_k = 1$. This ensemble combines:

• **Linear Regression (LR)** — baseline trend and seasonality capture; interpretable.

• **Random Forest (RF)** — robust, fast non-linear mapping; tolerates noisy features.

• **LSTM** — models temporal dependencies and sequence patterns in demand history.

•**ANN** — captures complex nonlinear interactions across features .

• **Gradient Boosting (GB)** — powerful tree-based learner that often improves accuracy on tabular data.

2. Inventory Analysis Agent

Once demand is predicted, the second agent compares these forecasts with real-time inventory records stored in databases or spreadsheets. This comparison is conducted across all available warehouses (e.g., W1, W2, W3) to assess where sufficient inventory exists to meet the forecasted demand. It compares $\widehat{D}_i$to warehouse inventories I_{ij}(product $i$at warehouse j), compute gaps:

$$G_{ij} = I_{ij} - \widehat{D}_i \qquad (8)$$

Flags: $G_{ij} < 0$indicates understock; $G_{ij} \geq 0$suffices for forecasted demand.

3. Coordination Agent

This is the decision-making core of the system. Based on inputs from the first two agents, it determines:

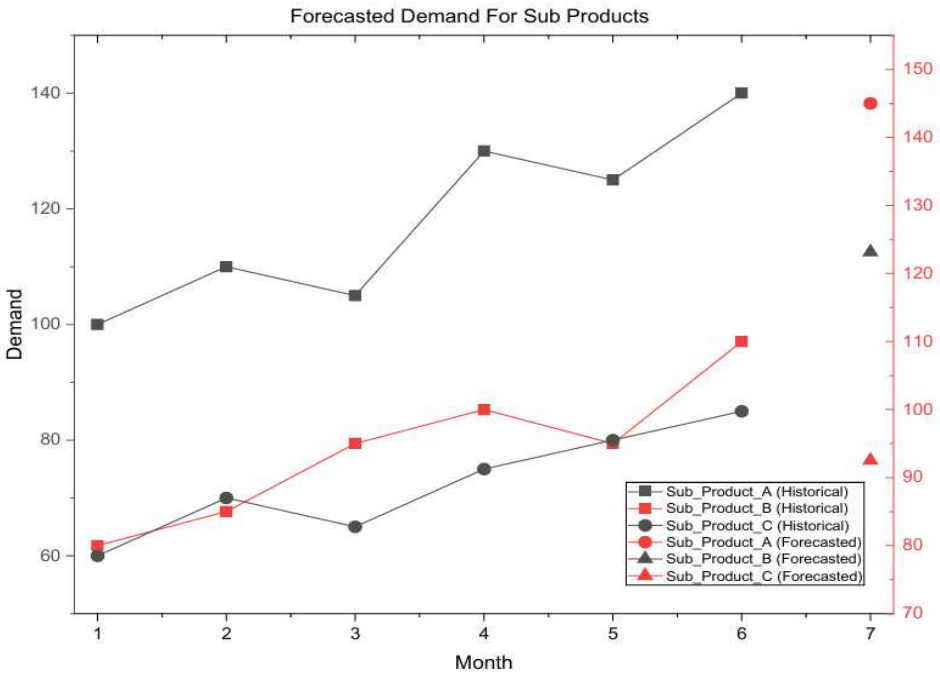
- Which warehouse is best positioned to fulfill the demand for each sub-product
- Whether a shortage exists
- Recommendations for procurement or inter-warehouse transfers

The Coordination Agent can also trigger alerts to human planners, suggesting when and where action is needed well before production bottlenecks occur.

It minimizes redistribution and procurement cost while satisfying demand:

$$Z = \sum_i \quad \sum_j \quad c_{ij}\left(0, -G_{ij}\right) \tag{9}$$

subject to capacity $I_{ij} \leq Cap_j$and aggregated availability $\sum_j \quad I_{ij} \geq \widehat{D}_i$ where feasible as given in (9) . The engine recommends: best warehouse to fulfill $\widehat{D}_i$, inter-warehouse transfers, or procurement actions and generates alerts when supply is insufficient.



3.5 Results and Discussion

Fig 9: Forecasted sub-product demand with real-time visualization

Predicted Demand for Next Month

The system has used historical demand data for three sub-products (A, B, and C) and applied a forecasting model to predict the demand for the next (7th) month as shown in Figure 9 . The predicted values are:

- **Sub_Product_A**: 145.0 units
- **Sub_Product_B**: 112.5 units
- **Sub_Product_C**: 92.5 units

These forecasts are displayed alongside current inventories $I_{ij}$to produce gap scores $G_{ij}$and a normalized **risk score** $R_i$for each product (used by the Coordination Agent). A simple normalized formulation is given in (10):

$$R_i = \frac{max(0, \widehat{D}_i - \sum_j \quad I_{ij})}{\widehat{D}_i} \quad (range\ 0-1) \qquad (10)$$

Best Warehouse to Fulfill the Demand

The system compares the forecasted demand with the current inventory levels across available warehouses and provides a recommendation:

- **Sub_Product_A**: No warehouse has enough inventory to meet 145 units — action needed (e.g., reorder or redistribute).
- **Sub_Product_B**: The demand can be met by Warehouse **W3**.
- **Sub_Product_C**: The demand can be met by Warehouse **W1**.

These suggestions assist supply chain mangers in determining which warehouses would be able to meet the sub-product demands and where proactively taking actions such as ordering or reallocating is needed. In the suggested AI Agent-Based Supply Chain Coordination framework, an ensemble of different models- LSTM, ANN, Random Forest, and Gradient Boosting work together to predict the demand and mitigate uncertainty. LSTM handles time-varying and seasonal effects, ANN learns the complex relation between demand and its drivers, whereas Random Forest and Gradient Boosting deliver quick and robust predictions in tabular form. This allows agents to make fast and effective decisions even in cases of abrupt demand increases or disruptions in the supply chain. Training on the M5 Forecasting dataset provided by Walmart helped in replicating the industrial supply chain environment.

In **Fig. 10**, the variations of the risk scores of sub-products A, B and C have been illustrated in different monitoring intervals. An increase in score implies an increase in the shortage risk and vice-versa. Here, Sub-Product A has an increasing pattern, suggesting stock problem whereas, B and C remain largely stable. This makes it easy for planners to recognize early indications of stock problems and conduct prompt actions such as relocation or replenishment.

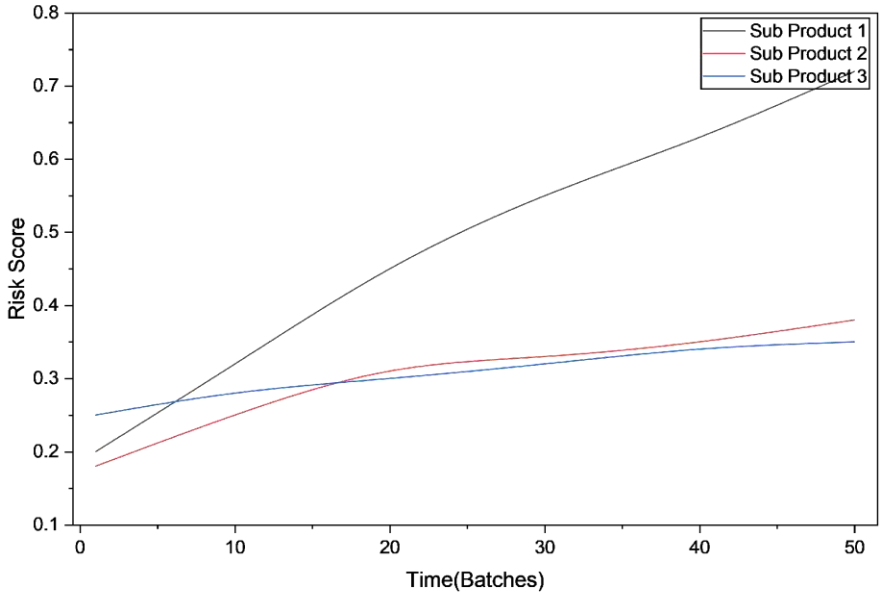


Figure 10 Risk Score Trends Over Time

From the loss curves of Figures 11, it is observed that both training and validation loss have decreased smoothly implying effective learning of the network. Moreover, the two curves follow one another closely, which implies good generalization without any sign of overfitting. However, small fluctuations may be noticed in both due to the natural nature of variation in time-series data.

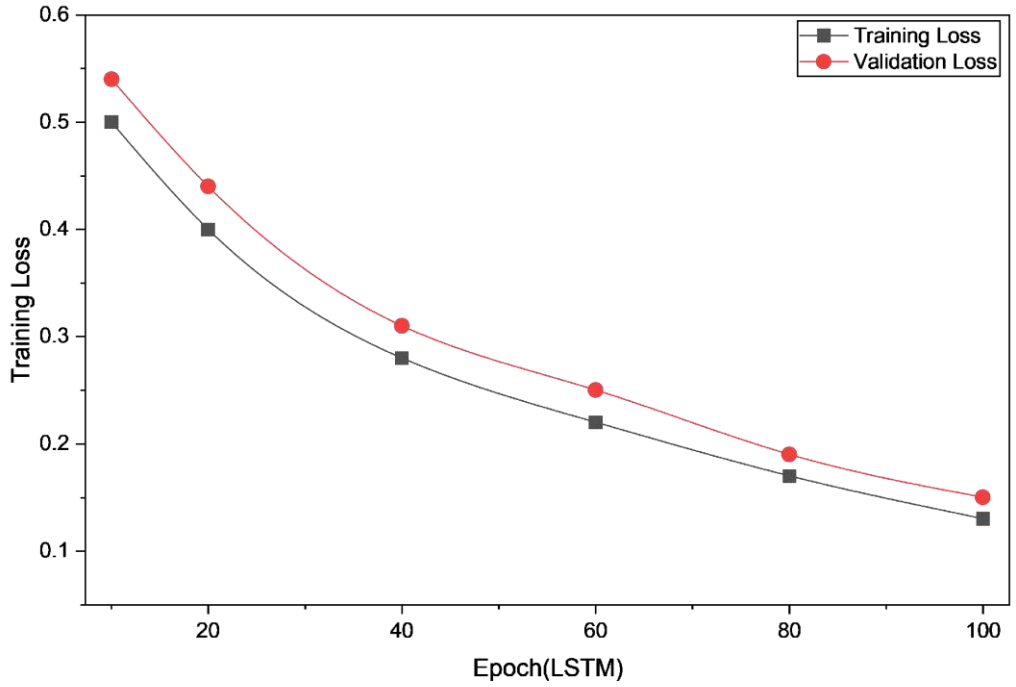


Figure 11 : LSTM Model Training Process Across Epochs

This means that we can now easily figure out which systems have shortages and manage accordingly. The ANN model was trained on the non-linear relationship between demand and inventory values. The accuracy curve of the model show that they were increasing steadily at high values during the training and validation phases. From Fig. 12, it can be observed that there is a very small gap between the two curves, which implies that the learning was well-balanced. thus , ANN would be capable of capturing complex patterns and making reliable prediction in the supply chain.

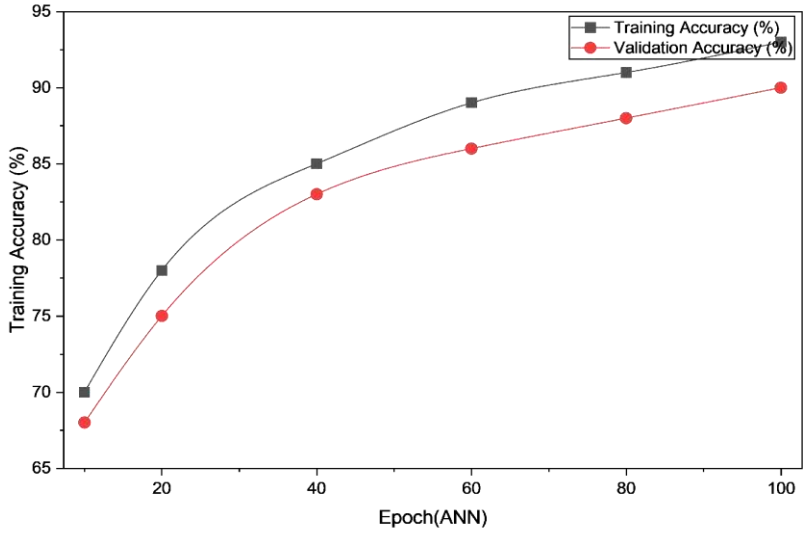


Figure 12 : ANN Model Training Process Across Epochs

In order to determine how effectively the AI Agent-Based Supply Chain Coordination system classifies the demand levels, a confusion matrix has been created with three classifications: Sufficient, Moderate and Critical Shortage. The Values on the diagonals indicate the correct classification while the other cells contain values indicating incorrect classification. As most of the values lie on the daigonals, it indicates that the model can classify the wel-stocked and poorly stocked systems as illustrated in Figure 13.

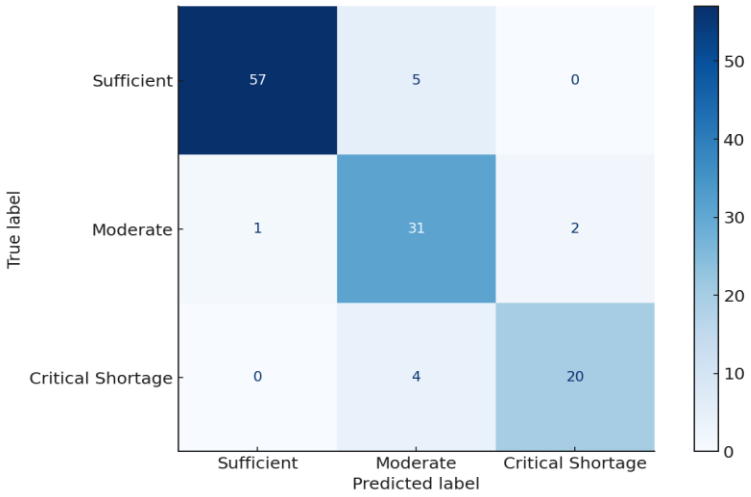


Figure 13 Confusion Matrix for AI Agent-Based Supply Chain Coordination System

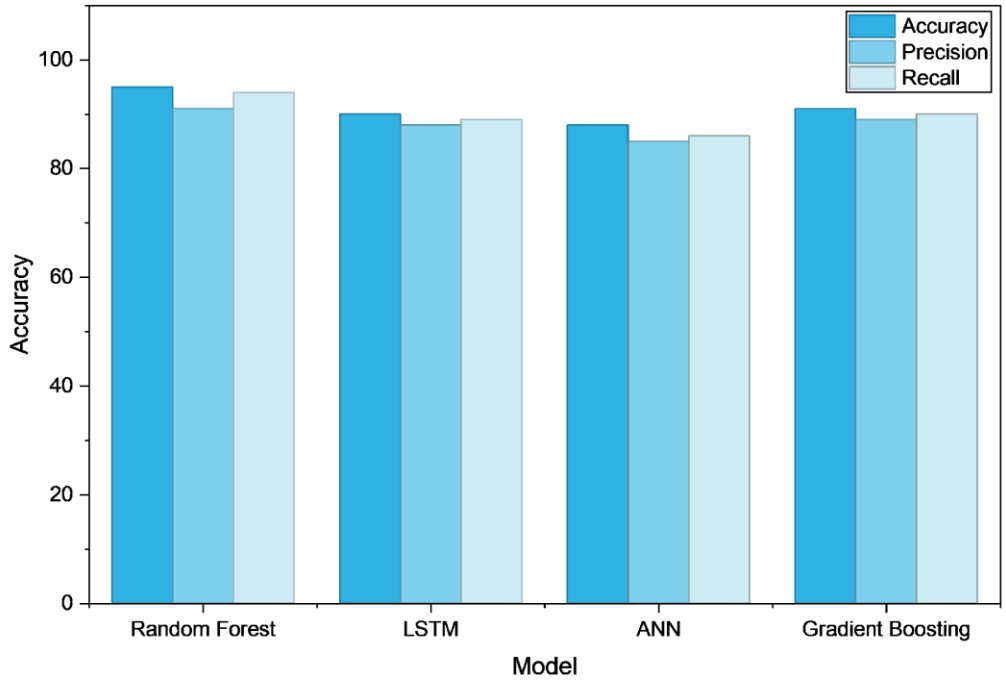


Figure 14 Performance Comparison Of The Models

As illustrated in Figure 14, four different machine learning models have been assessed to determine the optimal one. These four models, the model that gave the best result was the Random Forest, with an accuracy of 95% and precision of 91%, meaning it can handle demand variability quite effectively.

The LSTM model was good for the time based pattern recognition but could not cope with demand variability. ANN and Gradient boosting gave moderate results and would need some optimization.

4.Conclusion

From Supply chain optimization to the predictive maintenance and adaptive production planning, this paper has demonstrated how the development in artificial intelligence and intelligent agents is revolutionizing industrial engineering through smarter and more efficient decisions making processes.

The Findings from the experiments carried out for both the cases are evidence of this revolutionary change brought about by the integration of AI. In the Real-Time Predictive Maintenance Dashboard, for example, machine failures were predicted beforehand, thus reducing unexpected downtimes and enhancing maintenance efficiency. In addition, the AI Agent-Based supply chain coordination system was able to increase the availability of sub-products due to accurate prediction of demand and effective stock management.

With regard to the future developments in the Predicitve Maintenance System, there will be integration of IoT-based industrial sensors to collect and stream real time machine data into the dashboard. Communication and data synchronization will be done through cloud based APIs created via Fast API or Flask. Edge computing will be adopted near production floors.

For the AI Agent-Based supply chain system, emphasis will be placed on integrating real-time inventory management by developing strong REST APIs and scaling up by deploying on cloud based platforms like AWS or Azure. Real time analytics at the edge will speed up decision making processes. In Subsequent versions, complex AI technologies like reinforcement learning and self-organizing multi-agent systems will be applied to make the system capable of adapting to unforeseen changes in demand, logistics or other external disturbances.

Ultimately, combining AI with IoT and intelligent collaboration techniques marks a significant advance towards intelligent, self-developing industrial ecosystems.

Declarations

a. Funding

‘Not applicable’

b. Conflicts of interest/Competing interests

‘Not applicable’

c. Authors' contributions

All authors contributed to the study conception and design. Data collection, and the implementation of the intelligent agents were performed by Supriya and Sharanya Shree. The first draft of the manuscript was written by Sharanya Shree. Supervision and critical revisions for intellectual content were provided by Dr. Soma Prathibha and Dr. K. Palanikumar. All authors read and approved the final manuscript.

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